A Novel Multidimensional Clustering based Dynamic Destination Recommender System employing Optimization Techniques

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CERTIFICATE

This is to certify that the thesis entitled "A Novel Multidimensional Clustering Based Dynamic Destination Recommender System Employing Optimization Techniques" is a bonafide record of research work carried out by Ms. Bhoomi M Bangoria (Enrol. No. 220810340002), Research Scholar, Department of Computer Engineering, School of Engineering and Technology, Dr. Subhash University - Junagadh, under our supervision/guidance during the period July 2022 - November 2025. To the best of our knowledge: (I) the candidate has not submitted the same research work to any other University or Institute for any Degree, Diploma, Associateship, Fellowship or other similar titles (II) the thesis submitted is a record of original research work done by the Research scholar during the period of study under our supervision, and (III) the thesis represents independent research work on the part of the Research scholar.

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DECLARATION

I, Ms. Bhoomi M Bangoria, Research scholar in the Department of Computer Engineering, declare that the work embodied in the Ph.D. thesis entitled, "A Novel Multidimensional Clustering Based Dynamic Destination Recommender System Employing Optimization Techniques" is my original and bonafide work carried out by me under the supervision of Prof. (Dr.) Sweta S Panchal, Associate Professor, Dept. of E & C Engineering, Dr. Subhash University and the co supervision of Prof. (Dr.) Sandipkumar R Panchal, Professor, Dept. of E & C Engineering, Dr. Subhash University for a period from July 2022 to November 2025 at Dr. Subhash University.

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Index

Certificate ……..…… ii

Declaration ……... iii

Index ……. iv

List of Figures …….. vi

List of Tables …… vii

Abstract……. viii

Chapter 1 Introduction ……..……... 1

1.1 Brief of Recommender System …… 1

1.2 Destination Recommender Systems: An Overview …… 2

1.3 Optimization Techniques ……. 4

1.4 Motivation for the Study …….. 4

Chapter 2 Literature Review ……..... 5

2.1 Introduction ……. 5

2.2 Advance in Recommender System …….. 5

2.3 Research Gap Analysis …… 8

2.4 Objectives of the Study …… 9

2.5 Scope of the Work ……... 10

Chapter 3 Multidimensional Clustering based Dynamic DRS……. 11

3.1 Overview of the Study ……. 11

3.2 Research Problem: Towards a Multidimensional Clustering based Dynamic DRS ... 11

3.3 Optimization Techniques ……. 12

Chapter 4 Significance of the Dynamic DRS…… 13

4.1 Significance of the Study ……. 13

Chapter 5 Methodology of Research and Result……... 16

5.1 Methodology …… 16

5.1.1 Dataset and Pre-processing …….. 16

5.1.2 Algorithms Used …….. 16

5.1.3 Hybrid Algorithms ……... 18

5.2 Results and Discussion …… 20

5.2.1 Clustering Visualization ……... 20

5.2.2 Evaluation Metrics ……... 20
5.2.3 Quantitative Comparison ……. 20
5.2.4 Model Validation ……. 21
Chapter 6 Conclusion and Future Scope ……...….... 22
6.1 Conclusion ……..……. 22
6.2 Future Scope …… 22
Paper Publication Details…….. 23
References……. 24

List of Figures

Figure 1.1	Types of RS ……...	1
Figure 4.1	Proposed System Architecture ……...	14
Figure 5.1	K-Means Clustering Algorithm …….	17
Figure 5.2	The Elbow Method Graph …….	17
Figure 5.3	Weighted K-Means Clustering Algorithm ……	17
Figure 5.4	DBSCAN Clustering Algorithm ……	17
Figure 5.5	OPTICS Clustering Algorithm ……..	17
Figure 5.6	K-Means Clustering Algorithm with ABC Algorithm ……..	18
Figure 5.7	K-Means Clustering Algorithm with PSO Algorithm ……...	18
Figure 5.8	Weighted K-Means Clustering Algorithm with ABC Algorithm …….	19
Figure 5.9	Weighted K-Means Clustering Algorithm with PSO Algorithm ……..	10

List of Tables

Table 1.1 Advanced Features in Recent DRSs ……... 3
Table 5.1 Quantitative Comparison of Hybrid Algorithms …… 20

Abstract

This study aims to suggest the best travel destinations to users based on their preferences in different areas like city name, type and significance. To do this, a special method is used that combines recommendation techniques with clustering. We use weighted K-means clustering algorithm along with optimization approaches like Artificial Bee Colony (ABC) and Particle Swarm Optimization (PSO) for the finer tuning of clusters. Weight or scaling factor adjust the contribution of each feature to the overall distance calculation. Results show that the use of optimization techniques improves the performance. The data source contains different city names. Using Python's geolocation tool, each city's latitude and longitude are found to make clustering more accurate. The elbow method helps to decide the right number of clusters. Weighted K-means with PSO delivered the best result as shown in the experiment, yielding a very efficient method for generating the accurate and relevant destination choices. This proposed technique might rely upon more ubiquitous and inclusive code inspection regarding other relative strategies which appear by wording of significant appraisal measures. Greater precision means the algorithm finds more useful stuff without too many false positives, while higher accuracy means it asks better questions and gets most of its answers right. Having a better memory allows this to recall more relevant events and the higher F1 score indicates that both recall and precision are up. A reduced Mean Absolute Error (MAE) further highlights the efficiency and durability of the strategy by reducing variance from real values and improving forecast consistency.

Chapter 1

Introduction

1.1 Brief of Recommender System

Recommender systems are useful tools for filtering and recommending relevant information to users [1]. They may be particularly effective if the number of items (or options) is very large and users would benefit from personalized recommendations based on their preferences and interests [2]. AI Recommender systems can take various AI techniques and machine learning algorithms to process user data and provide recommendations [1]. Most liked websites and carriers include Spotify, youTube, netflix, Google, flipkart, Amazon and Gaana. com use recommender systems to recommend music, videos, products and others to users. Thanks to its users' generated data, these systems can provide personalized recommendations and help users to discover new content and make informed choices. Recommender systems are generally categorized as three different types' viz. content-based recommender systems, collaborative-filtering recommender systems and hybrid recommender systems [2-3].

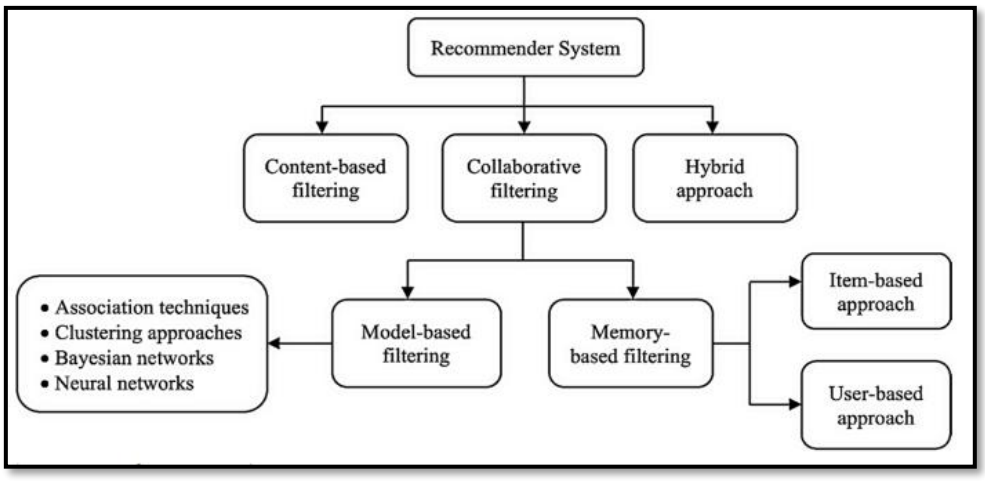

Figure 1.1 Types of RS [2]

Recommender systems (RSs) for travel and tourism have significantly evolved in recent years, shifting from traditional collaborative filtering approaches to more personalized, context-aware, and optimization-driven models. The technologies being adopted now include multidimensional clustering, deep learning, and multi-objective optimization, which are designed to improve the

quality of recommendations, particularly in the dynamic and real-time contexts [11-21].

Multidimensional Clustering for Tourist Preferences: A number of studies apply clustering methods, including K-means and density-based techniques, to categorize users or locations based on preferences, geography, seasonality, and travel behavior. The formation of these clusters aids in narrowing the scope of recommendations and increasing the accuracy of personalization. [20].

Integration of Optimization Techniques: To enhance the quality of the clusters formed, optimization techniques have been used to address the static clustering problem. These algorithms optimize intra-cluster similarity and inter-cluster separation, thus improving the overall effectiveness of cluster-based recommender systems.

Dynamic Recommendation and Context Awareness: The latest destination recommender systems are increasingly more dynamic, responding to changes in user preferences in real time. Systems such as the Destination Finder let users make updates to preferences in real time and are able to provide adaptive recommendations on the spot. This level of user control is increasingly becoming a hallmark of state-of-the-art recommender systems [12-13].

Deep Learning and Spatio-Temporal Modeling: To analyze complex user behaviors, deep learning models such as GRUs and attention networks are used to analyze sequential check-ins, repeat visits, and other temporal data. One such model, the Spatio-Temporal Intention Learning Self-Attention Network (STILSAN), employs self-attention and spatial encoders to learn preference and intention patterns [19].

Sustainable and Fair Recommendations: To date, integrating multi-objective optimization for itinerary planning which considers environmental issues such as tourism, carbon footprint, and tourism seasonality, received little attention. A sustainability-aware RS was proposed by Banerjee et al., integrating over tourism, carbon emissions, and seasonality into destination recommendations [21].

1.2 Destination Recommender Systems: An Overview

A Destination Recommender System (DRS) helps users identify suitable travel destinations or points of interest (POIs) by analyzing personal preferences, behaviour, context (like time and location), and in recent works, sustainability. Modern DRSs have moved from simple rule-based systems to data-driven, AI-powered, and context-aware solutions.

Table 1.1 Advanced Features in Recent DRSs

Feature	Description
Preference-Intention Learning	Differentiates between exploring new places and revisiting past favorites [19]. It improves the **accuracy** of recommendations by making them more in line with the user's genuine travel plans.
Serendipity and Diversity	Promotes novelty and unexpected recommendations [14]. It helps to maintain **precision** by delivering new yet helpful suggestions that reduce down on outputs that aren't beneficial.
Sustainability & Fairness	Penalizes high-emission, over-touristed, or high-season destinations [25]. It helps to **recall** that the suggestions are fair, which can aid with memory by presenting a wider range of relevant choices, including less popular but still useful places to visit.
Visual Exploration Interfaces	Allows users to explore POIs via maps and graphs in real-time [12]. It helps people choose, which in turn enhances the **F1-Score** by enhancing both precision and recall in a balanced way.
Cold-start Resolution	Uses clustering, Bayesian models, or demographic priors to recommend to new users [16]. It lowers the **MAE** by accurately predicting what new users or users or locations will like. This makes the suggestions more reliable and consistent. This makes the suggestions more reliable and consistent because people will prefer the places they suggest.

Based on the research, the following directions are considered cutting-edge:

- Understand how recommendation methods work and how well they match users' interests
- Create a smart destination recommendation system that uses many different factors
- Show users a list of travel options based on what they like
- Use clustering techniques to group similar users or destinations

- Apply optimization techniques to improve performance metrics like accuracy, precision, recall, F1-Score and MAE.

1.3 Optimization Techniques

Optimization strategies are ways to maximize or minimize an objective function, subject to particular restrictions, in order to discover the optimum solution for a problem [2]. By using iterative updates to identify the optimal answer, these algorithms assist models in learning from data. In this research, following optimization techniques are used:

- Artificial Bee Colony (ABC) Algorithm: Inspired by the foraging behavior of honeybees, ABC improves the search for optimal cluster centroids, enhancing convergence and preventing the algorithm from getting stuck in local minima.
- Particle Swarm Optimization (PSO): Based on the collective intelligence of swarms, PSO efficiently explores the solution space to identify globally optimal clustering results, improving both accuracy and robustness.

1.4 Motivation for the Study

Numerous factors, including user interests, geography, budget, and even current conditions like weather and seasonality, influence travel choices. Conventional recommender systems frequently use static data, which restricts their customisation and flexibility. There is a great demand for an intelligent system that can handle this multifaceted complexity because user preferences are dynamic and ever-changing. The objective of this research is to create a machine learning-based destination recommender system that can adjust to shifting circumstances, increase accuracy, and boost user happiness in the travel industry.

Chapter 2

Literature Review

2.1 Introduction

Recommender systems (RS) are pivotal in helping users navigate vast data spaces by suggesting personalized items such as products, movies, destinations, or social connections [1, 2]. Basic approaches extracted from the literature are:

- Content-Based Filtering (CBF): Takes the characteristics of items and the expressed preferences of users into account. It has drawbacks of overspecialization, small discovery and heavy reliance on well-developed metadata [1, 4].
- Collaborative Filtering (CF): Anchors on user-item interactions (such as ratings). It has been effective, but is restricted by cold-start (no prior data) and sparsity issues [4, 5].
- Hybrid Filtering: Fuses CBF and CF to take advantage of their correctness, but it makes the model more complex. Most popular hybrid methods are based on the sequential filtration, linear combination and unified model [4, 5].

2.2 Advance in Recommender System

Advances in RS research in recent years are as follows:

Sentiment and Opinion Mining: For addition of user responses, reviews and natural language opinions, particularly, in travel and tourism domain [2, 4].

Adaptive Neuro-Fuzzy Inference Systems (ANFIS): Hybrid intelligence systems (e.g. ANFIS) offer the researchers a flexible, interpretable and adaptive model that can be effectively executed while handling uncertain vague, imprecise, or incomplete data, thereby generating more personalized and reliable travel recommendations [3].

More route attributes and traffic scenarios need to be considered before recommending appropriate routes to meet the increasing personalized requirements of self-drive tourists [6].

Method employs opinion-mining technology to access user sentiment tendency for tourism destinations, and makes use of temporal dynamics to model the use of preferences and item popularity changing overtime [7].

Boost the social network so that additional features of social relationships can be fetched from other social networks, discovering the members who are alike [8].

The study also identified a necessity for increased privacy and security concerns when designing new recommender systems as the level of personalization and contextualization are becoming extended using Artificial Neural Network (ANN) [9].

One area of future work is to adapt the destination filter setting or their rated filters for destinations concomitantly with ratings of accommodations and attractions similar to the proposed weighting [10].

The Mobile Tourism E-Commerce Recommendation (MTERec) model provides a systematic, adjustable, and contextually aware method for giving personalised travel guidance. Its actual integration of social trust, temporal patterns, and geolocation knowledge enables more intelligent, user-centric, and flexible solutions in the digital tourist sector [11].

The Destination Finder application provides an innovative, user-friendly way to explore travel destinations by dynamically adapting to user preferences in real time. Future versions could consider real-time factors like user location, weather conditions at the destination, or travel time and cost and machine learning algorithm [12].

By integrating deep learning with topic modelling, geolocation analysis, and user behaviour patterns, the proposed Deep Learning-based recommendation Model (DLM) to recommend minority tourist routes based on users' preferences gathered from social networks. For enhance scalability, Optimize the model to handle larger datasets across more cities or travel types [13].

This paper introduces a powerful and innovative solution to make travel recommendations more engaging, exciting, and satisfying by incorporating serendipity. Instead of just repeating familiar options, the Serendipity-Oriented Personalized Trip Recommendation (SOTR) model recommends a balanced mix of relevant, novel, and unexpected Points of Interest (POIs), creating a trip plan that feels both useful and adventurous. In future, Context-Aware Recommendations which include real-time factors such as: weather, location etc. [14]. In my research work, I considered location as one of the input parameter.

The Hybrid Offer Ranker (THOR) is a smart, adaptive, and hybrid recommendation system that goes beyond simple POI suggestions. Perfect travel offers are ranked and the rankings adapted to each user, with the autocompletion of ranking tables based on observed preference clashes and solving the cold-start by clustering. Built for performance on standardized tests and with a modular design that indicates further use in the physical world, it is well positioned for real-world applications like mobility-as-a-service (MaaS) solutions and travel organizers. In addition, use multimodal deep learning for enhanced cluster Recommendations [15].

Now, travelers have so many choices when planning a trip to somewhere new. Especially for short-term tourists because they don't have a clear idea of what types of museums, parks, or cafes suit their interest? The proposed system is implemented in a real mobile app called Visit Planner (ViP), aimed at visitors in Agios Nikolaos, Crete [16]. Present study is on one city [16]. Subsequent iterations will employ the system in additional sites in other to establish generalisability [16].

The system of route finding over several points of interest with an objective to maximize total reward is the focus of the optimization and planning problem and is referred to as the multi-day categorised orienteering problem with count-dependent rewards. Finally, the effectiveness of the proposed integrated recommender system in suggesting personalized multi-day itineraries is demonstrated through a comprehensive evaluation on a real-world dataset based on Tehran [17].

The authors advocate the creation of a general framework that allows convenient specification of the TRSs, possibly with support of software engineering methodologies, low-code tools or AI-based virtual assistants. Such advancements could make TRSs more adaptive, scalable, and effective across various tourism settings. In future, better handling of real-time data like traffic updates, weather, and user movement should be easily integrated into TRSs [18].

This paper introduces a powerful and innovative model Spatio-Temporal Intention Learning Self-Attention Network (STILSAN) which considers not just user preferences but also their revisiting intentions, while incorporating spatial and temporal information. Future improvements suggested, Improve model generalization using external contextual features like time of day, event calendars, or weather [19].

This study outperforms existing systems (like TripAdvisor or Google Maps) by offering context-aware, accurate, and user-specific suggestions. The use of a data-driven machine learning approach, a multi-model strategy, and an easy-to-use algorithmic framework makes this system valuable for both travellers and tourism planners in Nepal. For future direction, Use visitor ratings

and behaviour to retrain models and improve recommendations and extend the system to other cities and rural tourist areas [20].

This paper presents a practical framework to make tourism sustainable and socially fair, by combining travel emissions, city popularity, and seasonality into a single recommendation model. This shows how recommender systems can be used to combat over tourism and encourage responsible travel decisions. Authors suggest these extensions such as addition of accommodation, food, and activity- related emissions; Expand the methodology to global cities outside Europe; Include data that varies (in real-time) like weather or local events [21].

Classic hotel recommender systems (that rely on reviews, votes, video views etc.) fail in most of the categories (as these are textual + numeric data). Collaboration Filtering + scrapper for Sentiment Analysis around Review Forums and Fuzzy Logic with Hadoop, Cassandra to use for Offline Big Data when suggesting Hotels based both on numerical as well textual feedback [22].

As with most e-commerce recommender systems, diversity, scalability, trust, privacy, and system growth are often simultaneously neglected alongside accuracy. An evaluation of 33 research papers revealed 5 types of recommendation techniques (CF, CBF, DBF, KBF, Hybrid) and their accompanying strengths, weaknesses, and future gaps [23].

2.3 Research Gap Analysis

Despite rich contributions, there are unresolved issues and underexplored directions relevant to developing a novel multidimensional clustering-based dynamic destination recommender system:

1. Lack of Multidimensional Clustering Frameworks: Existing systems apply clustering on a single dimension (e.g., user ratings, demographic, or behavioural features) but do not simultaneously incorporate contextual, social, temporal, and preference dimensions for clustering, which are crucial for dynamic destination recommendation [1-3].
2. Limited Adaptivity and Real-Time Optimization: Most RS are static or periodically updated. Few integrate real-time optimization algorithms (PSO, ABC, GA etc.) to adaptively modify clusters and optimize recommendations based on streaming or frequently updated input data [4-5].
3. Insufficient Evaluation on Quality Metrics: Most systems rely on MAE, RMSE, and precision. But, critical qualitative aspects such as novelty, diversity, serendipity,

confidence scores, and user trust are not well maintained or judged, particularly in the travel recommendation scenarios [4].

4. Integration of Clustering and Optimization: A number of studies put emphasis on clustering (e.g., k-means, hierarchical clustering) to enhance:
    - Scalability by grouping similar users/items
    - The prediction performance given the localized similarity computations
    - Contextual user group based personalization

Abstract the research project "A Novel Multidimensional Clustering Based Dynamic Destination Recommender System Employing Optimization Techniques" directly meets the gaps mentioned above by:

- Utilizing multidimensional context features for high-precision clustering (e.g., the name, type, and significance of a city).
- To evaluate cluster using elbow method to find optimal cluster number and K-means clustering technique with scaling factor for determining clusters.
- Employing optimization algorithms to continuously improve recommendations and cluster boundaries.
- In order to find an optimised spot, the search procedure is completed using the ABC algorithm.
- Users are given relevant item or content recommendations by the PSO algorithm based on their interests.

2.4 Objectives of the Study

- To design and develop proposed destination recommender system which can incorporate multiple parameters.
- To evaluate cluster using elbow method to find optimal cluster number and weighted K-means clustering technique with scaling factor for determining clusters.
- To find best evaluation parameters, optimization techniques are to be implemented.
- To analyze recommendation method that can accurately predict user preferences.
- To identify recommendation list of user’s preferences.

2.5 Scope of the Work

The scope of a destination recommender system is vast and multi-dimensional, providing value across different sectors:

- Personalized Travel Suggestions: These systems can offer personalized recommendations based on user preferences and interests, improving user satisfaction.
- Data-Driven Insights: By analyzing large datasets, such systems can identify emerging travel trends, popular destinations, and preferences, allowing users to make informed decisions.
- Enhancement of User Experience: Offering tailored suggestions enhances the user experience by simplifying decision-making, allowing users to discover destinations they may not have considered.
- Business Opportunities: Tourism businesses (hotels, airlines, etc.) can integrate these systems to attract customers, boosting revenue through targeted marketing strategies.
- Increased Tourism: Countries or regions can utilize destination recommenders to promote lesser-known tourist spots, thereby spreading tourism benefits more evenly across regions.
- Sustainability: By recommending eco-friendly destinations and travel methods, these systems contribute to sustainable tourism and environmental conservation efforts.
- Real-Time Updates: Systems can offer up-to-date information regarding travel restrictions, weather, and events, providing travellers with reliable and timely recommendations.
- Global Reach: These systems cater to a global audience, expanding their utility across various cultures, languages, and preferences, thus having broad international potential.

Chapter 3

Multidimensional Clustering based Dynamic DRS

3.1 Overview of the Study

This method improves the accuracy of cluster formation recommendations by utilizing optimization techniques in conjunction with a weighted K-means clustering algorithm and a hybrid filtering system. This study made use of a data set that takes into account various city names, types, and significance. According to citynames, latitude and longitude are obtained for accurate clustering in Python by utilizing a geolocator object.

3.2 Research Problem: Towards a Multidimensional Clustering based Dynamic DRS

- Dynamic Destination Recommender System revolves around the complexity of providing personalized travel recommendations to users based on various dynamic factors. Traditional recommendation systems often rely on static data, offering limited personalization and adaptability. In the travel industry, user preferences, location, time constraints, budget, and real-time events such as weather or seasonality all play crucial roles in determining ideal destinations.
- However, recommending suitable travel destinations becomes a challenge when multiple variables are involved, making it difficult to capture, process, and analyze this multidimensional data accurately. Additionally, travellers' preferences are not static and may change over time, adding to the complexity of providing relevant suggestions.
- The goal is to develop a recommendation system that adapts dynamically to these shifting preferences and external factors using machine learning techniques like clustering and optimization. By segmenting users and destinations based on common attributes or behaviours, the system can offer tailored recommendations that evolve with users' needs.

3.3 Optimization Techniques

In order to find the best solution for a problem, optimization procedures involve maximizing or minimizing an objective function while adhering to specific constraints. These algorithms help models learn from data by determining the best solution through iterative updates. The following optimization strategies are applied in this study:

- ABC: This approach, which is modeled after honeybee foraging, enhances convergence and keeps the algorithm from being trapped in local minima while improving the search for ideal cluster centroids.
- PSO: PSO effectively searches the solution space to find globally optimal clustering results, enhancing accuracy and robustness. It is based on the collective intelligence of swarms.

The problem thus focuses on leveraging multidimensional data, dynamic user profiles, and machine learning clustering techniques to build a more effective and personalized destination recommender system using optimization techniques.

Chapter 4

Significance of the Dynamic DRS

4.1 Significance of the Study

The study presents a novel contribution to the field of destination recommender systems by integrating optimization techniques with clustering algorithms. It introduces a hybrid filtering system that employs weighted K-means clustering enhanced with Artificial Bee Colony (ABC) and Particle Swarm Optimization (PSO) to improve recommendation accuracy.

The research highlights the limitations of traditional recommender systems in handling multi-dimensional user preferences and proposes an optimized clustering framework that dynamically adjusts feature weights for more personalized recommendations.

A key contribution is the improvement in clustering accuracy—the study demonstrates that weighted K-means with PSO achieves 93% accuracy, outperforming traditional K-means approaches. Additionally, it introduces a scaling factor to modify the Euclidean distance calculation, ensuring better feature representation in clustering.

The study also employs the elbow method to determine the optimal number of clusters, enhancing the precision of destination recommendations.

Compared to existing models, the proposed approach improves precision and recall by 6%, demonstrating its effectiveness in recommendation systems.

These findings have broader implications beyond tourism, extending to e-commerce, urban planning, and other multi-objective decision-making domains, making the research a valuable contribution to the field of machine learning-driven recommendations.

In the user interface, first users have to enter the city of their choice and select criteria like restaurants, hotels, historical places, and others. After submitting these data, the request goes to backend services.

Proposed system architecture is shown below:

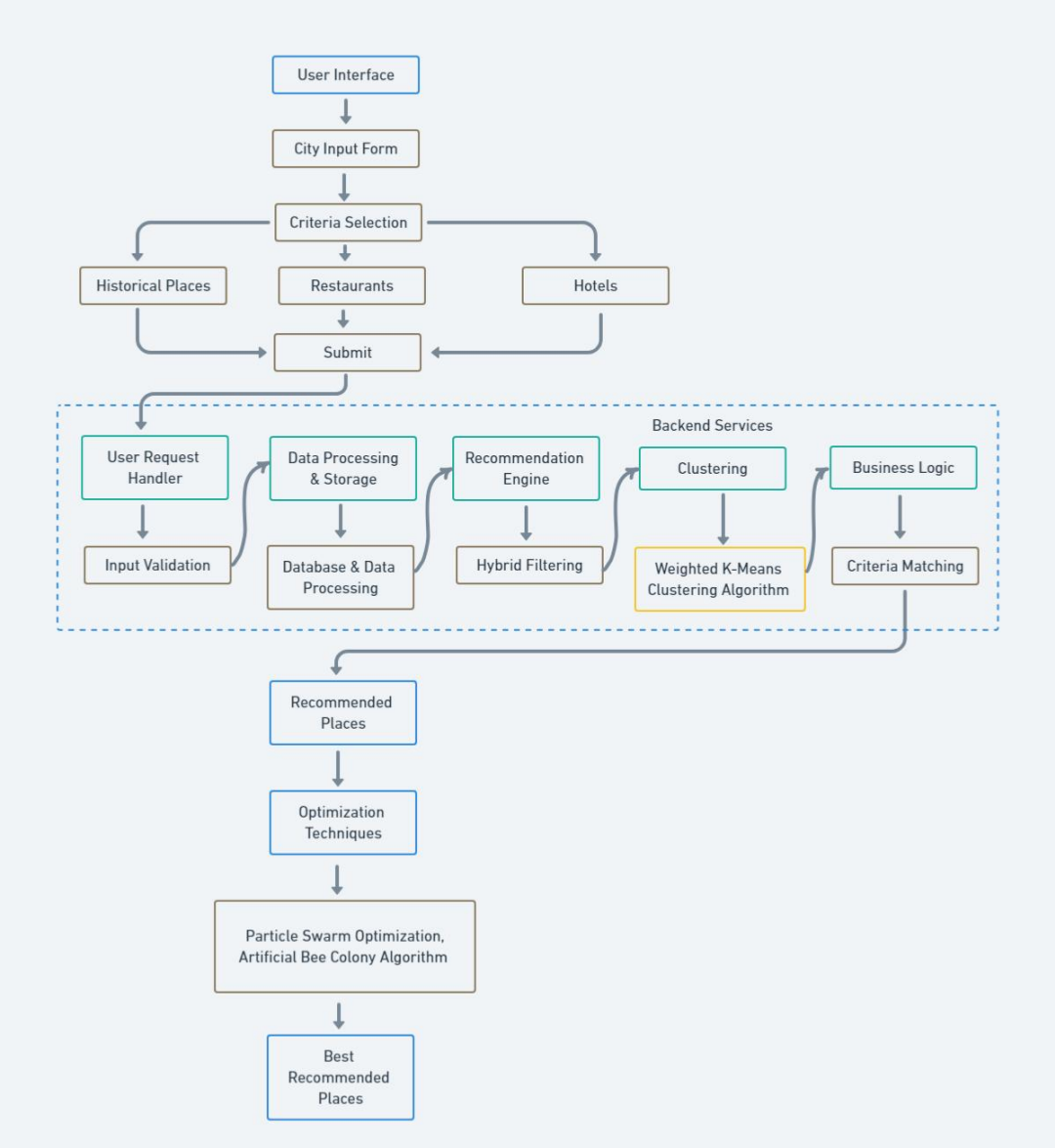

Figure 4.1 Proposed System Architecture

In backend services, first, check for input data validation, check it in the database, and process the data. Then after applying hybrid filtering techniques for recommendation. In clustering, used a weighted K-means clustering algorithm which used scaling factor and elbow method to discover an ideal number of clusters. We extend the Euclidean distance formula by introducing a scaling factor that adjusts the contribution of each feature to the whole distance calculation. This scaling

factor is a parameter that reflects the importance or relevance of each feature from the perspective of the clustering task. After that use business logic in which it considers criteria matching with user preferences. Utilized optimization techniques for best recommendation. At last, the system recommends places according to user preferences.

Chapter 5

Methodology of Research and Result

5.1 Methodology

The research methodology is centered on developing a hybrid dynamic destination recommender system (DRS) using advanced clustering and optimization techniques. The objective is to identify optimal destination recommendations based on user-defined preferences spanning multiple dimensions.

5.1.1 Dataset and Pre-processing

The study employs a dataset titled "Guide to India's Must-See Places," comprising city names, destination types, and significance. Geolocation data (latitude and longitude) is fetched using a geolocator API in Python for spatial clustering. All features are standardized using Z-score normalization to ensure uniformity in distance calculations.

5.1.2 Algorithms Used

This study compares three clustering algorithms: K-means, Density Based Spatial Clustering of Applications with Noise (DBSCAN) and Ordering Points to Identify the Clustering Structure (OPTICS). After the study of partitioning and density-based methods, it shows that simple statistical data are used in density-based algorithms. DBSCAN is well-suited for identifying clusters of arbitrary shapes by identifying 'core' and 'border' points in a dataset, core points are those that have a sufficient number of neighbors within a specified radius, while border points are those connected to core points but lacking their dense neighborhood while OPTICS provides a hierarchical density-based cluster ordering. However, the partitioning method was chosen for this study due to its ability to efficiently cluster large datasets with spatial data, particularly after enhancing it with feature weights. In this study, the weighted K-means clustering algorithm is used for proposed work.

A. K-means Clustering Algorithm:

Basic K-means is used as a baseline to identify clusters in user-destination feature space. However, its limitations in handling varying feature importance and convergence quality necessitate enhancements.

B. Weighted K-means Clustering Algorithm:

This version modifies standard K-means by assigning weights to features. A weighted Euclidean distance metric is used to emphasize or de-emphasize specific features based on their significance.

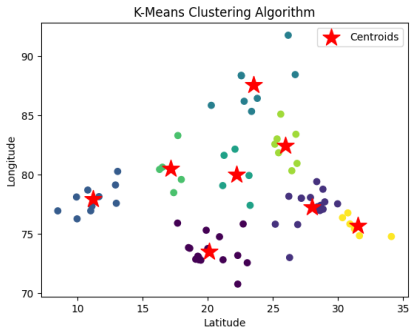

Figure 5.1 K-Means Clustering Algorithm

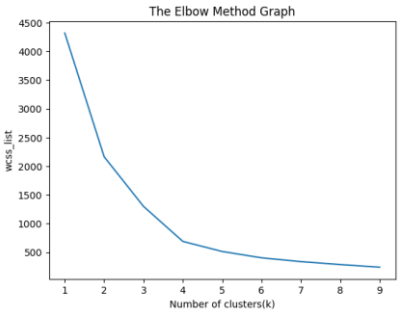

Figure 5.2 The Elbow Method Graph

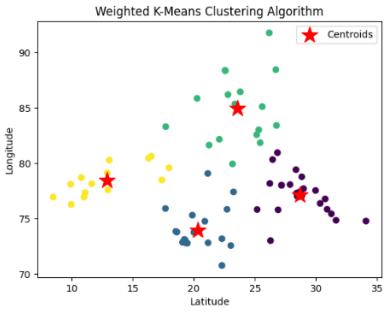

Figure 5.3 Weighted K-Means Clustering Algorithm

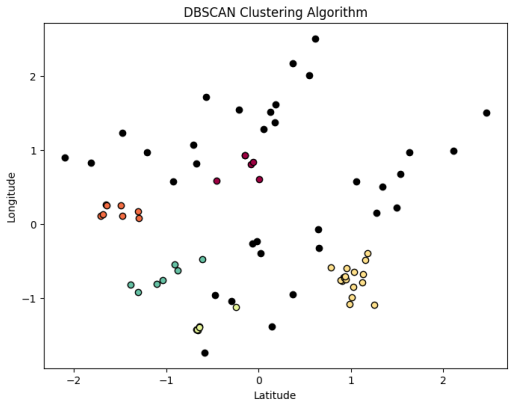

Figure 5.4 DBSCAN Clustering Algorithm

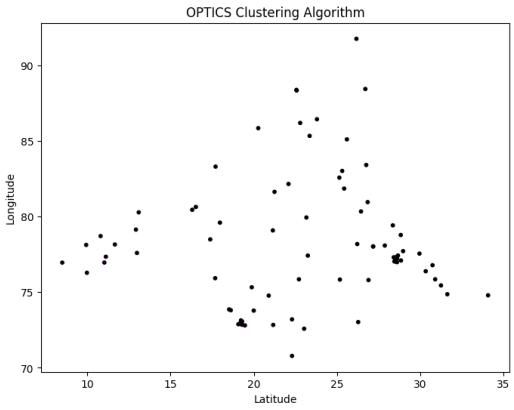

Figure 5.5 OPTICS Clustering Algorithm

C. Optimization Techniques

Two evolutionary algorithms are integrated to improve clustering outcomes:

• Artificial Bee Colony (ABC): Mimics bee foraging behavior to explore optimal cluster centroids and feature weights.

• Particle Swarm Optimization (PSO): Uses a population of particles to move through solution space, updating based on individual and group bests.

Both techniques help address local optima and improve the initialization and refinement of cluster centers.

5.1.3 Hybrid Algorithms

A. K-means + ABC

The ABC algorithm is used to generate initial centroids. The final positions from the bee colony are refined using one iteration of K-means to optimize assignment.

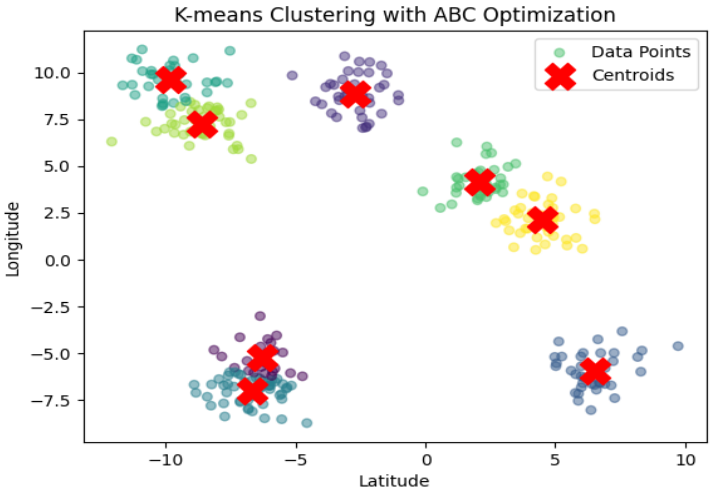

Figure 5.6 K-Means Clustering Algorithm with ABC Algorithm

B. K-means + PSO

Particles represent candidate centroids. Updates use PSO velocity-position rules. Final output is refined via K-means.

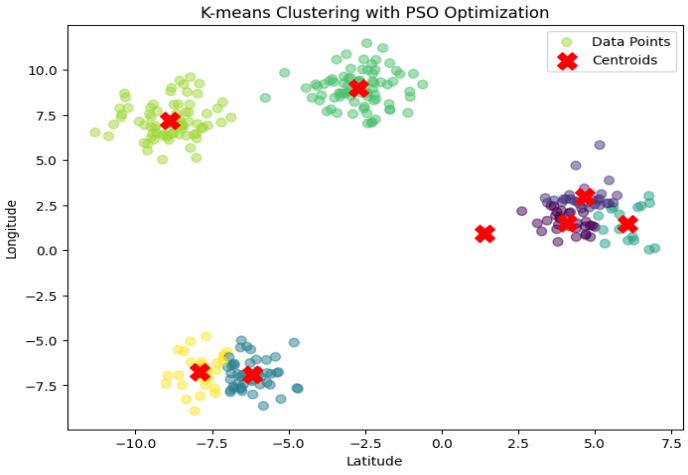

Figure 5.7 K-Means Clustering Algorithm with PSO Algorithm

C. Weighted K-means + ABC

In this hybrid, ABC optimizes both centroids and feature weights. Each solution is evaluated using Within-Cluster Sum of Squares (WCSS), and the elbow method determines optimal cluster count.

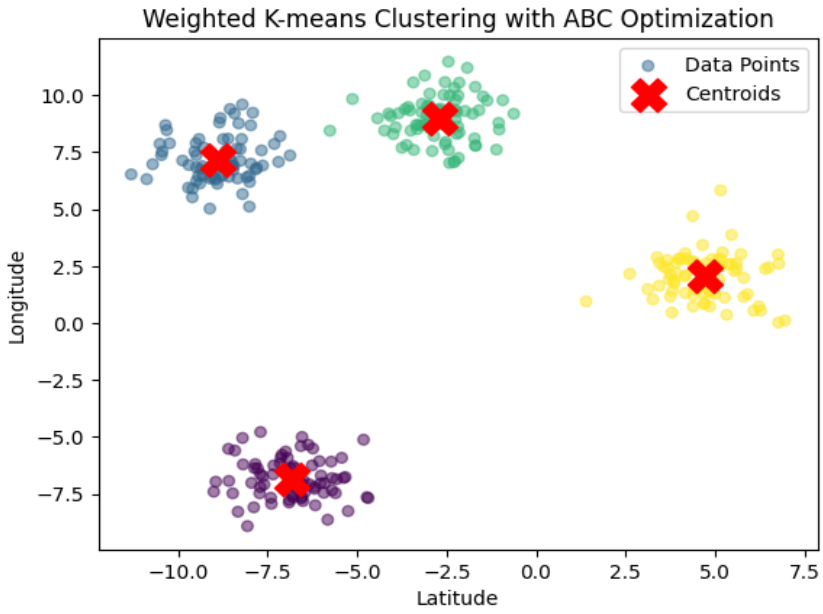

Figure 5.8 Weighted K-Means Clustering Algorithm with ABC Algorithm

D. Weighted K-means + PSO

Particles encode both weights and centroids. Fitness is WCSS, optimized through standard PSO update equations. The elbow method is used to select the best number of clusters.

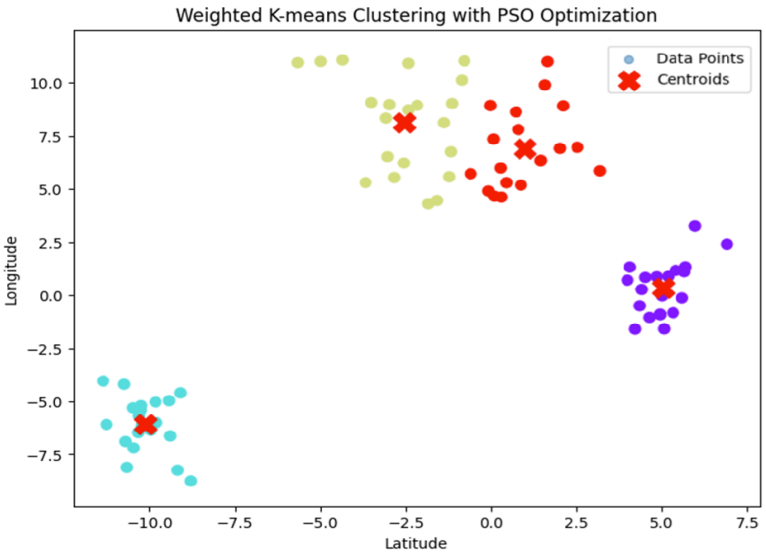

Figure 5.9 Weighted K-Means Clustering Algorithm with PSO Algorithm

5.2 Results and Discussion

5.2.1 Clustering Visualization

Figure 5.8 & Figure 5.9 show how the different methods form clusters with centroids optimized by ABC or PSO. The color-coded dots represent clustered data, and red crosses denote centroid locations. Spatial coordinates (latitude, longitude) are used in visualization.

5.2.2 Evaluation Metrics

The following metrics are used to evaluate clustering and recommendation performance:

- Accuracy (ACC): Proportion of correct recommendations.
- Precision (P): Proportion of relevant destinations among those recommended.
- Recall (R): Proportion of relevant destinations that were recommended.
- F1-Score (F1): Harmonic mean of Precision and Recall.
- Mean Absolute Error (MAE): Average absolute difference between predicted and actual user satisfaction.

5.2.3 Quantitative Comparison

Table 5.1 Quantitative Comparison of Hybrid Algorithms

Metric	K-means + ABC	K-means + PSO	Weighted K-means + ABC	Weighted K-means + PSO
Accuracy	0.85	0.88	0.90	**0.93**
Precision	0.80	0.85	0.87	**0.91**
Recall	0.78	0.83	0.85	**0.90**
F1-Score	0.79	0.84	0.86	**0.90**
MAE	0.12	0.10	0.09	**0.07**

Weighted K-means with PSO shows the best performance across all metrics, demonstrating the strength of feature weighting and PSO's exploratory power.

5.2.4 Model Validation

The final model, Weighted K-means + PSO, achieves 93% accuracy, validating its effectiveness for multi-criteria recommendation scenarios. It is adaptable, scalable, and suitable for real-time applications.

Chapter 6

Conclusion and Future Scope

6.1 Conclusion

To sum up, this research introduces a smart, flexible, and optimized recommendation system that adapts to the user's personal interests using dynamic feature weighting and nature-inspired optimization techniques. In Weighted K-means Clustering Algorithm, the scaling factor w_i adjusts the contribution of each feature to the overall distance calculation and used Elbow method to find optimal number of clusters. By combining weighted K-means clustering with ABC and PSO, the system achieves better clustering and more accurate destination recommendations. The system shows a noticeable improvement in accuracy and has strong potential in many other fields beyond tourism. The findings show that optimisation strategies in conjunction with weighted clustering outperform simple K-means. When compared to other methods, the Weighted K-means with PSO methodology yields the most improved and dependable results, with more accuracy and reduced error.

6.2 Future Scope

The study opens the door for future improvements, such as integrating real-time data sources, including location-based information, social media trends, seasonal fluctuations, and user preferences, is one such approach. As a result, the system would be able to produce extremely dynamic and context-aware recommendations that are constantly modified to account for shifting circumstances. A further noteworthy prospect is the implementation of more sophisticated optimisation techniques than those presently in use. New approaches that could improve cluster formation and suggestion accuracy, including deep reinforcement learning, evolutionary algorithms, or hybrid metaheuristics, could result in more reliable performance in intricate and big datasets. Lastly, creating interactive and user-friendly interfaces would improve the system's accessibility and appeal.

Paper Publication Details

1. Bangoria BM, Panchal SS, Panchal SR, Bangoria TM. (2024) A Novel Machine Learning Approach for Multidimensional Dynamic Destination Recommender S earch System Employing Clustering using Optimization Techniques. Indian Journal of Science and Technology. 17(44): 4679-4693. https://doi.org/10.17485/IJST/v17i44.3525

2. Bangoria BM, Panchal SS, Panchal SR, Maheta JM, Dhabaliya SR. (2024) Multidimensional Dynamic Destination Recommender Search System Employing Clustering: A Machine Learning Approach. Indian Journal of Science and Technology. 17(40): 4187-4197. https://doi.org/10.17485/IJST/v17i40.2266

3. Bhoomi M. Bangoria, Dr. Sweta S. Panchal, Dr. Sandipkumar R. Panchal, Sweety R. Dhabaliya (2023). A comprehensive study of the destination recommender system employing artificial intelligence. 3rd International Conference on Women in Science & Technology: Creating Sustainable Career (ICWSTCSC: 2023) at BVM, Vallabh Vidyanagar, Anand during 28 – 30 December, 2023

4. Bhoomi M. Bangoria, Dr. Sweta S. Panchal, Dr. Sandipkumar R. Panchal, Sweety R. Dhabaliya (2024). A study of AI-powered destination recommender system. 2nd International Conference on Emerging Trends & Contemporary Practices (ICETCP: 2024) at Atmiya University, Rajkot

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